Synopsis for Registration as Research Student

for

Doctoral Degree

on

Retinal Image Analysis for Hypertensive Retinopathy Detection

by

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1. Introduction

Hypertensive retinopathy is a condition characterized by a spectrum of retinal vascular signs in people with elevated blood pressure. The detection of hypertensive retinopathy with the use of an ophthalmoscope has long been regarded as part of the standard evaluation of persons with hypertension. Hypertensive retinopathy was first described by Marcus Gunn in the 19th century in a series of patients with hypertension and renal disease. The retinal signs he observed included generalized and focal arteriolar narrowing, arteriovenous nicking, flame shaped and blot-shaped retinal hemorrhages, cotton-wool spots, and swelling optic disk.

The retina is the tissue layer located in the back of your eye. This layer transforms light into nerve signals that are then sent to the brain for interpretation. When your blood pressure is too high, the retina's blood vessel walls may thicken. This may cause your blood vessels to become narrow, which then restricts blood from reaching the retina. In some cases, the retina becomes swollen. Over time, high blood pressure can cause damage to the retina's blood vessels, limit the retina's function, and put pressure on the optic nerve, causing vision problems. This condition is called hypertensive retinopathy (HR).

Symptoms of hypertensive retinopathy

You probably won't have any symptoms until the condition has progressed extensively. Possible signs and symptoms include:

- reduced vision
- eye swelling
- bursting of a blood vessel
- double vision accompanied by headaches

2. Motivation

Essential or primary hypertension, the world's leading risk factor for global disease burden, is expected to cause more than half of the estimated 17 million deaths per year resulting from cardiovascular disease (CVD) worldwide. Defined as an elevation of blood pressure (BP)

beyond 140/90 mm Hg, hypertension is strongly correlated with adverse outcomes such as stroke, ischemic heart disease, heart failure, and end stage renal disease. The challenges of managing hypertension and preventing the development of these latter outcomes are unlikely to relent; the global burden of hypertension is projected to increase by 60% to affect approximately 1.6 billion adults worldwide by 2025.

considerable hurdles remain in overcoming the burden of hypertension. First, the insidious nature in which hypertension develops means that hypertension is frequently undiagnosed, and early detection prior to the development of end-organ damage remains a challenge. Second, many patients appropriately diagnosed with hypertension fail to achieve the treatment targets recommended by guidelines. This highlights the considerable challenges in implementing risk factor modification and appropriate adherence to antihypertensive therapies long term. Third, uncertainty remains as to the appropriate BP treatment target for high-risk patients. So, an automatic method based on digital image processing will be faster and need less (no) human intervention, which can yield more consistent results.

3. Literature Survey

Debasis Maji et al, [1] proposed tortuosity-based grading using Convolutional Neural Network (CNN) model. The proposed method is validated on a public dataset EIARG1.

Kanae Fukutsu et al, [2] developed a novel evaluation system for retinal vessel alterations caused by hypertension using a deep learning algorithm . fundus photographs were analyzed using a fully automatic architecture assisted by a deep learning system, and the total area of retinal arterioles and venules was assessed separately. The retinal vessels were extracted automatically from each photograph and categorized as arterioles or venules. Subsequently, the total arteriolar area (AA) and total venular area (VA) were measured. The correlations among AA, VA, age, systolic blood pressure (SBP), and diastolic blood pressure were analyzed. Using the algorithm, a significant positive correlation was found between AA and VA. Both AA and VA demonstrated negative correlations with age and blood pressure. Furthermore, the SBP showed a higher negative correlation with AA measured by the algorithm than with AVR.

Guangzheng Dai et al, [3] developed detection method for the effect of hypertension on retinal microvasculature using deep learning. study suggested that the effect of hypertension on retinal microvascular morphology mainly occurred at branching of vessels. The change of the branching pattern of retinal vessels was probably the most

significant in response to elevated blood pressure. In collected 2012 retinal photographs which included 1007 from patients with a diagnosis of hypertension and 1005 from normotensive control. Method of vessel segmentation is used to removed interference information other than retinal vasculature and contained only morphological information about blood vessels. segmented images are used to trained a small convolutional neural networks (CNN) classification model and used a deep learning technique called Gradient-weighted Class Activation Mapping (Grad-CAM) to generate heat maps for the class "hypertension". Our model achieved an accuracy of 60.94%, a specificity of 51.54%, a precision of 59.27%, and a recall of 70.48%. The AUC was 0.6506.

Syahputra et al, [4] proposed Probabilistic Neural Network (PNN) for identifying hypertensive retinopathy through retinal fundus images. Before the identification process, the image processing and feature extraction used in the proposed method are box counting and invariant moments. Based on the experiment result, the proposed method has been able to identify hypertensive retinopathy with the accuracy reached 100%.

Fraz et al, [5] presents a new supervised method for segmentation of blood vessels in retinal photographs. This method uses an ensemble system of bagged and boosted decision trees and utilizes a feature vector based on the orientation analysis of gradient vector field, morphological transformation, line strength measures, and Gabor filter responses. The feature vector encodes information to handle the healthy as well as the pathological retinal image. The method is evaluated on the publicly available DRIVE and STARE databases, frequently used for this purpose and also on a new public retinal vessel reference dataset CHASE_DB1 which is a subset of retinal images of multiethnic children from the Child Heart and Health Study in England (CHASE) dataset. The performance of the ensemble system is evaluated in detail and the incurred accuracy, speed, robustness, and simplicity make the algorithm a suitable tool for automated retinal image analysis.

Qaisar Abbas et al, [6] developed an automatic recognition system for detection of hypertensive retinopathy using dense features transform and deep-residual learning. the statistical analysis is performed on 4270 retinal fundus images through sensitivity (SE), specificity (SP), accuracy (ACC) and area under the receiver operating curve (AUC) metrics. The significant results were achieved compare to state-of-the-art methods. On

average, the SE of 93%, SP of 95%, ACC of 95% and 0.96 of AUC values were obtained through a 10-fold cross-validation test.

Uzma GuIzar Abbasi et al, [7] present a novel method for classification of Blood Vessels as Arteries and Veins for Diagnosis of Hypertensive Retinopathy. It contains five steps, images acquisition, vessel Extraction model, ROI detection Model, AVR computation model, then diagnosis of hypertension.

Bambang Krismono Triwijoyo et al, [8] proposed Detection of Hypertension Retinopathy Using Deep Learning and Boltzmann Machines. The proposed method is to determine the combined features artery and vein diameter ratio (AVR) as well as changes position with Optic Disk (OD) in retinal images.

Muhammad Usman Akram et al, [9] present data on fundus images for vessels segmentation and detection of hypertensive retinopathy. The data contains 100 high quality fundus images which are acquired from Armed Forces Institute of Ophthalmology (AFIO), Rawalpindi Pakistan. it contains highly detailed annotations for retinal blood vascular patterns, arteries and veins to calculate arteriovenous ratio (AVR), optic nerve head (ONH) region and other retinal anomalies such as hard exudates and cotton wool spots etc.

Qazaleh Mirsharif et al, [10] present Automated characterization of blood vessels as arteries and veins in retinal images . The proposed method consists of three main steps. In the first step, several image enhancement techniques are employed to improve the images. Then a specific feature extraction process is applied to separate major arteries from veins. Indeed, vessels are divided to smaller segments and feature extraction and vessel classification are applied to each small vessel segment instead of each vessel point. Finally, a post processing step is added to improve the results obtained from the previous step using structural characteristics of the retinal vascular network. In the last stage, vessel features at intersection and bifurcation points are processed for detection of arterial and venular sub trees. Ultimately vessel labels are revised by publishing the dominant label through each identified connected tree of arteries or veins. Evaluation of the proposed approach against two different datasets of retinal images including DRIVE database demonstrates the good performance and robustness of the method.

Li Zhang et al, [11] developed neural network for Prediction of hypertension, hyperglycemia and dyslipidemia from retinal fundus photographs . 1222 high-quality retinal images and over 50 measurements of anthropometry and bio-chemical parameters

were generated from 625 subjects. The models in this study achieved an area under the ROC curve (AUC) of 0.880 in predicting hyperglycemia, of 0.766 in predicting hypertension, and of 0.703 in predicting dyslipidemia.

Muhammad Arsalan et al, [12] aiding the diagnosis of diabetic and hypertensive retinopathy using artificial intelligence-based semantic segmentation. It presents a dual-residual-stream-based vessel segmentation network (Vess-Net), To evaluate the proposed Vess-Net method, experiments were conducted with three publicly available datasets for vessel segmentation: digital retinal images for vessel extraction (DRIVE), the Child Heart Health Study in England (CHASE-DB1), and structured analysis of retina (STARE). Experimental results show that Vess-Net achieved superior performance for all datasets with sensitivity (Se), specificity (Sp), area under the curve (AUC), and accuracy (Acc) of 80.22%, 98.1%, 98.2%, and 96.55% for DRVIE; 82.06%, 98.41%, 98.0%, and 97.26% for CHASE-DB1; and 85.26%, 97.91%, 98.83%, and 96.97% for STARE dataset.

Samiksha pachade et al, [13] have created Retinal Fundus Multi-Diseases Image Dataset (RFMiD) for development of method for automatic ocular disease classification of frequent diseases. It is consisting of 3200 fundus images captured using three different fundus cameras with 46 conditions.

Ling-Ping Cen et al, [14] have developed deep learning platform (DLP) capable of detecting multiple common referable fundus disease and conditions in which DLP achieved frequency-weighted average score of 0.923 and sensitivity of 0.978.

Tahira Nazir et al, [15] have proposed approach of an automated disease localization and segmentation based on Fast region-based CNN with Fuzzy k-means clustering is presented.

Kanupriya Mittal et al, [16] have done survey on automated retinal image analysis and algorithms used to localize and segment features such as optic disc, optic cup, macula and fovea, retinal blood vessels, detection of microaneurysm, hemorrhages, exudates.

Skylar Stolte and Ruogu Fang [17] have done survey on medical image analysis in diabetic retinopathy. In particular stated that deep learning can give diagnosis earlier and with higher sensitivity and specificity.

Maryam Badar et al, [18] have presented review on deep learning techniques applied on 2-D fundus and 3-D optical coherence Tomography (OCT) retinal images classification. The methodologies are analyzed in terms of sensitivity, specificity, area under ROC

curve, accuracy and F score. Publicly available dataset is used such as DRIVE, STARE, CHASE_DB1, DRiDB, NIH, AREDS, MESSIDOR-2, E-OPTHA, EyePACS-1, DIARETDB and OCT image data set.

4. Identified Open Research problems

1. To determine Hypertensive Retinopathy Symptoms
2. Detection of Retinal blood vessel to determine Automatic diagnosis of retinal images for early detection of glaucoma, stroke, and blindness.
3. Retinal vessels segmentation
4. Classification of Hypertensive Retinopathy
5. Classification of Vessels as arteries and veins
6. Dataset Size and quality
7. Extract retinal features such as blood vessels ,optics disc and lesions

Hypertensive retinopathy is usually asymptomatic and is diagnosed on fundoscopic features. The following are signs of hypertensive retinopathy.

AV Crossing Changes

Salus's sign: Deflection of retinal vein as it crosses the arteriole.

Gunn's sign: Tapering of the retinal vein on either side of the AV crossing.

Bonnet's sign: Banking of the retinal vein distal to the AV crossing.

Arterial Changes

Decrease in the arteriovenous ratio to 1:3 (the normal ratio is 2:3).

Change in the arteriolar light reflex (light reflex appears as copper and/or silver wiring)

Retinal Changes

Retinal hemorrhages:

Dot-blot hemorrhages: Bleeding in the inner retinal layer

Flame shaped hemorrhage: Bleeding is in the superficial retinal layer

Retinal exudates:

Hard exudates: Lipid deposits in the retina

Soft exudates: These are also known as cotton wool spots which appear due to ischemia of the nerve fibers

Macular Changes

Macular star formation due to deposition of hard exudates around the macula.

Optic Nerve Changes

Optic disk swelling (also known as hypertensive optic neuropathy)

5. Problem Definition

The segmentation of blood vessels from retinal images is a difficult and time-consuming task for medical specialists when diagnosing diseases such as hypertension, diabetic retinopathy, and arteriosclerosis. Digital retinal imaging playing an increasingly prominent role in the diagnosis and treatment of eye diseases, the problem of extracting clinically useful information has become important. For example, classification of vessels as arteries and veins , calculate vessel width to measure AV ratio, retinal vasculature, optic disc boundary, macula and location of exudates help to define the character and extent of diseases like hypertensive retinopathy, diabetic Retinopathy and glaucoma, aiding diagnosis and treatment. Therefore, segmentation of these features becomes a key challenge for proper analysis, visualization and quantitative comparison

6. Future research plan

1) To automatically detect the following normal features in retinal image to improve the performance of pathology detection.
    a. Automatic detection of AV Crossing Changes
    b. Automatic detection of Arterial Changes
    c. Automatic detection of retinal blood vessels
    d. correct vessel segmentation
2) To automatically detect Retinal Changes
    a. Retinal hemorrhages:
    b. Dot-blot hemorrhages: Bleeding in the inner retinal layer
    c. Flame shaped hemorrhage: Bleeding is in the superficial retinal layer
    d. Retinal exudates:
    e. Hard exudates: Lipid deposits in the retina
    f. Soft exudates: These are also known as cotton wool spots which appear due to ischemia of the nerve .
3) To develop an automatic retinal analysis system to classify severity of the disease.
4) To develop retinal retrieval system to retrieve the similar image from the database as that of query image.

Current techniques of hypertensive retinopathy detection and assessment are mostly manual, expensive, and potentially inconsistent requiring highly trained grades to facilitate the process by searching large number of retinal images. It is hoped that the proposed system can assist

ophthalmologists to make diagnosis more effective and provide an automatic cost-effective tool for the mass screening of retinopathy

7. Conclusion

To build Retinal Image Analysis system, to extract normal and abnormal features of fundus images by applying various newly developed image processing and pattern recognition methods. This system extracts the fundal features such as retinal blood vessels, optic disk, cotton wool spot, exudates, hemorrhages and microaneurysms. The Retinal Image Analysis system detects and grades the severity of hypertensive retinopathy. Hence, this system can also function as an automatic tool for the mass screening of hypertensive retinopathy.

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